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# The environmental efficiency analysis of China's power generation sector based on game cross-efficiency approach

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ABSTRACT

China's unbundling reform in 2002 aimed to introduce competitiveness into the power industry. With the increasing concern about the environmental issue and climate change, the ability to balance the reduction of carbon emissions with economic benefits may to a great extent determine the competitiveness of power generation sector. This study first adopts the game cross-efficiency approach to evaluate the environmental efficiencies of the generation sector in China's 30 provinces. The results indicate that significant efficiency gap does exist among regions. It then employs a system generalized method of moments model to explore the determinants of their performance while eliminating the associated endogeneity issue. Considering the negative correlation between environmental efficiency and the thermal power ratio, the power mix should be adjusted gradually. The per capita regional GDP and capacity utilization rate are positive factors boosting the environmental efficiency. Accordingly, the incentive policies for clean energy development should be differentiated across regions according to their power mix, self-sufficiency ratio, and economic development situations.



## 1. Introduction

The history of power system reform reveals a process aimed at improving market mechanism and building good competition system. Such reforms not only take place in the developed world, such as the power reforms of England in the early 1990s (Yang and Pollitt, 2009), but also undertake in developing countries, such as Argentina, Brazil and Chile (Rudnick et al., 2005). Introducing market-oriented mechanisms has always been the aim of China's power reforms in recent decades. In 2002, the State Council issued the unbundling reform of "separating power plants from grids". This was the first attempt to establish a market-oriented mechanism and framed China's power management mechanism in the following 15 years. By dismantling the vertically integrated power system into independent companies, this policy aims to develop a competitive regional or even national wholesale electricity market where power plants would place bids into the market and gain grid-access priority according to the economic merit. In 2003 the State Power Corporation was dismantled and reorganized into 11 corporations according to their businesses, among which five were generation groups,[1] in an effort to intensify the competition and improve the production efficiency.

In general, China's unbundling reform has accomplished a degree of success in the generation sector (Xie et al., 2012; Zhao et al., 2015), and it has had significant positive effects in enhancing the efficiency of fossil-fired power plants (Du et al., 2013; Meng et al., 2016). Nevertheless, with significant increase in installed capacity, the power supply has exceeded demand since 2012 on the whole, especially in the north, northeast, and northwest of China where the wind resources are abundant but the wind power is frequently curtailed. The competition of power generation sector refers to the competitive relationship among the provinces once the national power supply and demand imbalance occurs, and the state monopoly is broken. In this case, the provinces with excess power supplies have to face fierce competition to some extent when these

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provinces endeavor to export their surplus power to the importing provinces in order to improve their efficiencies. It is necessary to objectively examine the performance of the generation sector in a competitive environment to improve its efficiency and provide some guidance for further reform.

To cope with the deterioration of the environment, there is a growing trend of incorporating environmental factors when analyzing the production efficiency of the generation sector. Despite the pillar role of the power industry in China's economy, it also contributes to a large share of the national carbon emissions. Carbon dioxide emissions have become a widespread concern in the world (Al-Amin et al., 2015; Kholod and Evans, 2016). Since the beginning of the 21st century, the corresponding proportion has remained at a level of over 40% (Yan et al., 2016; Yang and Lin, 2016). To reduce fuel consumption and air pollution, the 12th Five-Year Energy Development Plan set the power consumption goal for 2015 for the first time, and the power industry came into a new era of dual control for both generation and carbon emissions. In addition, China pledged to reduce the carbon intensity by 60–65% by 2030 compared to 2005 levels (Zhang, 2017).[2] From 2014 the state government officially included the $CO_2$ emission intensity reduction goals in the regional or industry indexes for the first time.[3] As one of the key industries for emission abatement, the power industry has introduced a quota control mechanism in implementing its development plan and allocating emission shares.[4] Under this circumstance, it is essential to supplement the productivity performance with environmental efficiency in evaluating the development of the generation sector.

This study adopts a data envelopment analysis (DEA) game cross-efficiency model to assess the environmental performance of China's power generation sector under dual control of generation and carbon emissions. Considering the differences in fuel quality, energy structure, and technology, it further explores the determinants affecting the productivity of the generation sector. Although the power plants are operated by the generation groups, the power generated is determined by the provincial grids where the plants are located. Moreover, the production plans and emission quotas are all implemented by the provinces, so the studies of the generation sector in China mainly involve provincial analysis (Lin and Yang, 2014; Sueyoshi and Yuan, 2015; Zhou et al., 2013). To the best of our knowledge, this is one of the pioneering attempts to take the competitiveness into consideration in evaluating the performance of the generation sector. The other contribution of this study lies in introducing the system generalized method of moments (SGMM) to eliminate the endogeneity among the provinces. The rest paper proceeds as follows. Section 2 reviews the related literature. Section 3 introduces the concept of game cross-efficiency and SGMM. Sections 4 and 5 present the empirical results and discussions. Section 6 presents our conclusions and puts forward some policy recommendations.

## 2. Literature review

There has been a consensus on the impact of the electricity industry on the environment, especially the impact on carbon emissions and global warming. Färe et al. (1996) evaluated the environmental performance of American fossil fuel-fired electric utilities where $CO_2$ emissions are considered in addition to emissions of $SO_2$ and $NO_x$. Various studies have been conducted about environmental and eco-efficiency. These studies can be classified into four groups: comparison among countries and analysis based on a regional, firm, or plant level. For the efficiency comparison among countries, most of the decision making units come from the same international organization (Ewertowska et al., 2016; Xie et al., 2014). As for the regional analysis, Bi et al. (2014) analyzed the energy and environmental efficiencies of China's provincial thermal power sectors simultaneously, and the results indicated that both of them are heavily affected by the geographical conditions. The studies of Zhou et al. (2013) and Lin and Yang (2014) also found that the environmental performance of provinces differed significantly. Comparatively, Chen et al. (2017) investigated the similarity of environmental performance among regions. In general, most of the studies have included the undesirable outputs in evaluating the environmental performance of the provincial power sectors. At the firm or plant level, Korhonen and Luptacik (2004) studied the performance of power plants when evaluating technological and ecological efficiencies while Du and Mao (2015) estimated the marginal $CO_2$ abatement cost of thermal power plants.

Among the listed literature, DEA is one of the most widely used and effective methods to conduct efficiency evaluation (Song et al., 2012; Liu et al., 2013). A typical characteristic of the energy and electricity industries is the production of undesirable outputs, which is among the most widely applied DEA areas (Zhou et al., 2008). With regard to the environmental issues, the economic index and environmental index are separated into input and output. If pollution exists in the output, it will be treated as an undesirable one and should be minimized (Song et al., 2018). Sueyoshi et al. (2017) summarized the DEA applications from the 1980s to the 2010s, and suggested that of 185 papers on electricity, 75 were combined analyses dealing with various environmental issues, such as greenhouse gas emissions and waste discharges. Such applications are implemented in other areas as well, such as water treatment (Molinos-Senante and Sala-Garrido, 2015) and industrial sectors (Camioto et al., 2014; Chen and Golley, 2014; Fan et al., 2015) and so on, which show that environmental efficiency has aroused widespread concern in various areas.

In addition, measuring efficiency without considering competition among provinces does not seem to provide objective results for efficiency benchmarking and comparisons. Chen et al. (2017) evaluated the energy efficiency of China's power industry considering the game relationship among provinces. Song and Wang (2017) emphasized the importance of competition, and pointed out that with China's huge degree of market liberalization over the last few decades, market competition has brought liveliness to industry development. Hence, this study adopts the game cross-efficiency model to measure the environmental performance of provincial power sectors and explores to give a specific rank of the generation sectors in a competitive power market. Compared to basic DEA, game cross-efficiency follows the peer evaluation concept of cross-efficiency in view of the similar features of the provincial generation sectors. In this way, the efficiency and ranking may properly reflect the competitiveness among DMUs.

Furthermore, the ultimate aim of efficiency evaluation for the power generation sector is to find the influencing factors and then put forward targeted measures to improve its performance. Many DEA studies have advocated a two-step approach where efficiency is estimated in the first step using linear programming, and then the estimated efficiencies are regressed on explanatory variables in the second step. For example, Yang and Pollitt (2009) analyzed the impact of the calorific value of coal and the unit scale on the environmental efficiency of power plants. Du and Mao (2015) ana-

[2] See the "Enhanced actions on climate change: China's intended nationally determined contributions" by National Development and Reform Commission in June 2015.

[3] See the "Carbon dioxide emission reduction per unit of GDP target responsibility assessment approach" issued by the National Development and Reform Commission in August 2014, in which the provincial $CO_2$ emission reduction per unit of GDP target is among the most important assessment indicators.

[4] See the "Greenhouse gas emissions control program during 13th Five Year Plan" by the State Council in November 2016.

lyzed the influences of factors including the ownership, scale, age, fuel structure, subsidy, location, and time trend on the efficiency.

In general, the previous literature mainly used Tobit regression (Fleishman et al., 2009; Zhao et al., 2015) to study the determinants of efficiency, under which the independent variable may lead to the endogenous issue because of the correlation between variables and the error term (Fan et al., 2015). To avoid this problem, some studies adopted the SGMM estimator in the second step (Chen and Golley, 2014; Fan et al., 2015). Meanwhile, SGMM is suitable for situations with "small T, large N" panels, meaning few time periods and many individuals (Roodman, 2009). To the best of our knowledge, this study is the first attempt to adopt game cross-efficiency approach in studying the efficiency of electric power industry. Also, it is the first time that SGMM has been rendered to analyze the determinants of the environmental efficiency for China's generation sector.

## 3. Methodology

### 3.1. The game cross-efficiency method

The basic DEA method groups the DMUs into efficient and inefficient sets, which cannot further discriminate the former group and it is apt to benefit itself in the choice of weight, however, the decision-makers are often interested in a complete ranking in order to refine the efficiency. DEA cross-efficiency is one of the popular approaches to achieve this goal (Liu et al., 2017), which was originated by Sexton et al. (1986) and further developed by Doyle and Green (1994). Cross-efficiency is a democratic process with less arbitrariness of additional weight restrictions.

Supposing that there are $n$ DMUs, the cross-efficiency method calculates the efficiency score of each DMU $n$ times using the optimal weights evaluated by the $n$ linear programming and then averages the results to get an average cross-efficiency score. It can avoid the disadvantages of basic DEA by both self and peer evaluation. To eliminate the non-uniqueness of cross-efficiency scores, aggressive and benevolent strategies have been proposed as secondary goals by minimizing or maximizing other DMU's efficiency at a second level. Liang et al. (2008) proposed a game cross-efficiency model based on the idea of cross-efficiency using game theory, which has been proved to be effective in getting a unique Nash equilibrium solution.

In an electricity market, each provincial generation sector can be treated as a producer (i.e. the DMU in a DEA model) with $m$ inputs and $s$ outputs, then $x_{ij}\,(i = 1, 2, \cdots, m)$ and $y_{rj}(r = 1, 2, \cdots, s)$ represent the $i$ th input and $r$ th output of $DMU_j\,(j = 1, 2, \cdots, n)$, and then the game cross-efficiency model can be expressed by formula (1):

$$\begin{aligned}
Max \quad & \sum_{r=1}^{s}\mu_{rj}^{d}y_{rj} \\
s.t. \quad & \sum_{i=1}^{m}\omega_{ij}^{d}x_{il} - \sum_{r=1}^{s}\mu_{rj}^{d}y_{rl} \geq 0, \quad l = 1, 2, \ldots, n, \\
& \sum_{i=1}^{m}\omega_{ij}^{d}x_{ij} = 1, \\
& \alpha_d \times \sum_{i=1}^{m}\omega_{ij}^{d}x_{id} - \sum_{r=1}^{s}\mu_{rj}^{d}y_{rd} \leq 0, \\
& \omega_{ij}^{d} \geq 0, \qquad i = 1, 2, \ldots, m, \\
& \mu_{rj}^{d} \geq 0, \quad r = 1, 2, \ldots, s,
\end{aligned} \tag{1}$$

where $\alpha_d$ is a parameter with an initial value given by the average original cross-efficiency of $DMU_d$, then use the average objective function value of formula (1) as the new value of $\alpha_d$ and repeat calculation, finally, it will converge to the best (average) game cross-efficiency. Here, the accuracy of convergence is set as 0.01, that is to say, if the difference between the two successive results is less than 0.01, then the latest $\alpha_d$ is considered as the optimal solution; $\alpha_d \times \sum_{i=1}^{m}\omega_{ij}^{d}x_{id} - \sum_{r=1}^{s}\mu_{rj}^{d}y_{rd} \leq 0$ ensures that, for each competing $DMU_j$, a multiplier bundle to optimize the efficiency for $j$ is determined with the additional constraint that the resulting score for $d$ should be at or above $d$' s estimated best performance. Therefore, this approach can be regarded as a form of a generalized benevolent approach.

For each $DMU_j$, formula (1) runs $n$ times, once for each $d = 1, 2, \cdots, n$, and for each $d$, it holds the constraint $\sum_{i=1}^{m}\omega_{ij}^{d}x_{ij} = 1$ for $DMU_j\,(j = 1, 2, \cdots, n)$. Hence, the game $d$-cross-efficiency for each $DMU_j$ can be defined by formula (2):

$$\alpha_{dj} = \frac{\sum_{r=1}^{s}\mu_{rj}^{d}y_{rj}}{\sum_{i=1}^{m}\omega_{ij}^{d}x_{ij}}, \qquad d = 1, 2, \cdots, n, \tag{2}$$

where $\mu_{rj}^{d}$ and $\omega_{ij}^{d}$ are the optimal weights for $x_{ij}\,(i = 1, 2, \cdots, m)$ and $y_{rj}(r = 1, 2, \cdots, s)$, respectively, in formula (1). Then the average game cross-efficiency of $DMU_j$ can be expressed by formula (3):

$$\alpha_j = \frac{1}{n}\sum_{d=1}^{n}\sum_{r=1}^{s}\mu_{rj}^{d*}(\alpha_d)y_{rj}. \tag{3}$$

This study aims to evaluate the performance of the generation sector. As well as the production efficiency, it is also necessary to take into account some byproducts that have adverse effects on the environment.[5] In this case undesirable outputs are incorporated into the game cross-efficiency model to maximize the $CO_2$ emission reductions when maximizing the power generation. Scheel (2001) summarized the DEA approaches with undesirable outputs and classified them as direct and indirect approaches. The indirect approaches use a monotone decreasing function $f$ to transform the undesirable outputs into "normal" outputs, through which increasing the transformed data means decreasing the original undesirable outputs. Following the indirect approaches of Liu et al. (2017), this paper incorporates undesirable outputs into DEA cross-efficiency, and applies the conversion function $f(U) = -U$, where $U$ represents the set of undesirable outputs. And then the following formula (4) can be obtained:

$$\begin{aligned}
Max \quad & \sum_{r=1}^{s}\mu_{rj}^{d}y_{rj} - \sum_{k=1}^{q}\nu_{kj}^{d}b_{kj} \\
s.t. \quad & \sum_{i=1}^{m}\omega_{ij}^{d}x_{il} - \left(\sum_{r=1}^{s}\mu_{rj}^{d}y_{rl} - \sum_{k=1}^{q}\nu_{kj}^{d}b_{kl}\right) \geq 0, \quad l = 1, 2, \ldots, n, \\
& \sum_{i=1}^{m}\omega_{ij}^{d}x_{ij} = 1, \\
& \alpha_d \times \sum_{i=1}^{m}\omega_{ij}^{d}x_{id} - \left(\sum_{r=1}^{s}\mu_{rj}^{d}y_{rd} - \sum_{k=1}^{q}\nu_{kj}^{d}b_{kd}\right) \leq 0, \\
& \omega_{ij}^{d} \geq 0, \quad i = 1, 2, \ldots, m, \\
& \mu_{rj}^{d} \geq 0, \quad r = 1, 2, \ldots, s, \\
& \nu_{kj}^{d} \geq 0, \quad k = 1, 2, \ldots, q,
\end{aligned} \tag{4}$$

where $b_{kj}\,(k = 1, 2, \cdots q)$ represents the $k$ th undesirable outputs of $DMU_j\,(j = 1, 2, \cdots, n)$, and $\nu$ is the corresponding weighting vector;

[5] This study mainly considers the environmental efficiency of the generation sector under the constraints of carbon abatement, and so $CO_2$ is treated as the only undesirable output.

the other settings are the same as formula (1). Formula (4) is able to achieve the expected results to minimize the undesirable outputs when maximizing the desirable outputs.

The game $d$-cross-efficiency of $DMU_j$ in this situation can be defined by formula (5):

$$\alpha_{dj} = \frac{\sum_{r=1}^{s} \mu_{rj}^{d} y_{rj} - \sum_{k=1}^{q} \nu_{kj}^{d} b_{kj}}{\sum_{i=1}^{m} \omega_{ij}^{d} x_{ij}}, \quad d = 1, 2, \ldots, n, \tag{5}$$

and the average game cross environmental efficiency score of $DMU_j$ can be expressed by formula (6):

$$\alpha_j = \frac{1}{n} \sum_{d=1}^{n} \left( \sum_{r=1}^{s} \mu_{rj}^{d*} (\alpha_d) y_{rj} - \sum_{k=1}^{q} \nu_{kj}^{d*} (\alpha_d) b_{kj} \right). \tag{6}$$

### 3.2. Driving factor analysis on SGMM

To avoid unobserved heterogeneity, omitted variable bias, and measurement errors when using the pooled ordinary least squares and fixed effect method, this paper uses SGMM to analyze the driving factor of environmental efficiency (Zhang et al., 2017). Arellano and Bond (1991) first proposed a different GMM (DGMM) estimator, which takes the previous efficiency as instruments. The SGMM estimator, an improvement of the DGMM estimator, was developed by Arellano and Bover (1995). Compared to DGMM, the SGMM allows more instruments to be introduced, thereby significantly improving the efficiency (Roodman, 2009). Meanwhile, the efficiency achieved from game cross-efficiency model and the explanatory variables might not be strictly exogenous. Thus, the SGMM is employed to do a second step analysis.

The SGMM model can be represented by formulas (7) and (8):

$$E_{i,t} = \alpha + \beta_0 E_{i,t-1} + \beta X_{i,t} + \mu_{i,t}, \tag{7}$$

$$\mu_{i,t} = \nu_i + \varepsilon_{i,t} \tag{8}$$

where $E_{i,t}$ represents the environmental efficiency of the $i$ th province in year $t$, and $E_{i,t-1}$ represents the lagged dependent variable. $E_{i,t-1}$ is used as an explanatory variable to exclude the impact of other historic independent variables so that the results represent the influence of the current period. $X_{i,t}$ refers to the vector of environmental explanatory variables, and $\mu_{i,t}$ is an error term representing the individual (provincial) influence, including the time-invariant individual characteristics $\nu_i$ and observed specific influence $\varepsilon_{i,t}$.

Several tests need to be carried out for SGMM: first, it is necessary to use the Arellano–Bond (AR) test to examine whether the residual series autocorrelation exists, and the null hypothesis is that the residual series has no autocorrelation. Second, SGMM is insensitive to first-order autocorrelation, but significant nth-order autocorrelation, usually second-order or third-order, in the residual series should be satisfied, because such an autocorrelation will make the lags of endogenous variables inappropriate. Besides, the instrument validity is directly tested by the Sargan (1958) or Hansen (1982) tests. However, the Sargan test statistic is suitable only when any disturbance assumed to be homoscedastic in a small sample. Taking this into consideration, the Hansen test is more suited to the assessment of instrument validity (Zhang et al., 2017). And then the Hansen test is performed to test the instrument validity and to ensure the validity of the results. Finally, Wald test is used to test the joint significance of variables.

**Table 1**
Summary statistics of inputs and outputs.

| Variable | Units | Max | Min | S.D. | Mean |
|---|---|---|---|---|---|
| Labor | Thousand | 120.40 | 3.020 | 24.08 | 34.83 |
| Installed capacity | GW | 85.98 | 1.76 | 19.19 | 26.62 |
| Energy | M tce | 148.02 | 1.42 | 29.42 | 35.48 |
| Power generation | TWh | 440.50 | 5.94 | 88.08 | 118.58 |
| $CO_2$ | Mt | 397.11 | 3.82 | 76.35 | 92.43 |

## 4. Empirical study

### 4.1. Data

This paper adopts the game cross-efficiency approach to analyze the environmental performance of the provincial generation sectors from 2003 to 2013. It includes 30 provinces in the study, which does not cover Taiwan, Hong Kong, Macao, and Tibet due to data availability. The starting year is set as 2003 since the competitive mechanism was introduced by the unbundling reform of 2002. Although the latest reform of power system was marked by the release of No. 9 document in 2015,[6] the number of pilot provinces that launched the direct power-purchase transaction pattern for large customers soared to 24 in 2014,[7] which indicates that the new reform had already begun at that time. The comprehensive implementation of direct power-purchase may have an impact on the competition of the generation sector. Therefore, this paper selects the time interval between the two reforms as the research period, which spans from 2003 to 2013. The non-energy inputs include capital and labor, and the capital is measured in terms of the installed generating capacity (Bi et al., 2014; Sueyoshi et al., 2017; Xie et al., 2012) which is derived from China's Electric Power Industry Statistics Compiled 2004–2014. Previous studies usually took the labor of electric power, gas and water production and supply as input (Bi et al., 2014; Lin and Yang, 2014), but this treatment does not accurately reflect the input of the labor force in the generation sector. Hence, the annual average of the total number of employees in the provincial generation sector is collected from the Macro China Industry Database[8]. The energy input is total fossil fuel consumption[9], which is gathered from the China Energy Statistical Yearbook 2004–2014 in terms of standard coal equivalent. The data for electricity generated are also collected from China's Electric Power Industry Statistics Compiled 2004–2014. As the focus is on the performance level under the constraints of carbon emissions reduction, this study adopts $CO_2$ emissions as the only undesirable output. In addition, $CO_2$ emissions of the generation sector are calculated according to IPCC (2006) with the emission coefficients of various kinds of fossil fuels considered[10]. Table 1 shows the basic statistics of inputs and outputs.

### 4.2. Results

The efficiency and statistics of the rankings obtained from the game cross-efficiency model are shown in Table 2. The results show

[6] No. 9 document refers to the "Opinions on Further Deepening the Reform of the Electric Power System" issued by the government on March 15, 2015. It proposed to guide market participants to develop direct power-purchase transaction patterns.

[7] Source: http://power.in-en.com/html/power-2242111.shtml.

[8] Source: http://mcid.macrochina.com.cn/.

[9] The energy consumption includes a variety of energy types, which is converted into standard coal in China Energy Statistical Yearbook. Due to the high proportion of coal-fired power in China's power mix, the impact on the results of oil and gas can be ignored.

[10] The net carbon emissions of 30 provinces for generations sector are almost the same as those of electric power industry issued by IEA, therefore the estimation is believable and trustworthy.

**Table 2**
Environmental efficiencies and rankings of provinces during 2003–2013.

| Province | Efficiency (Year) | | | | | | | | | | | Ranking | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | Mean | Max | Min |
| Beijing | 0.777 | 0.735 | 0.782 | 0.780 | 0.858 | 0.851 | 0.835 | 0.847 | 0.867 | 0.814 | 0.919 | 20.5 | 27 | 13 |
| Tianjin | 0.999 | 0.993 | 1.000 | 0.968 | 0.999 | 0.965 | 0.805 | 0.910 | 0.940 | 0.907 | 0.947 | 7.1 | 23 | 1 |
| Hebei | 0.909 | 0.957 | 0.935 | 0.899 | 0.913 | 0.878 | 0.847 | 0.859 | 0.841 | 0.84 | 0.840 | 13.7 | 22 | 6 |
| Shanghai | 0.971 | 0.977 | 0.946 | 0.914 | 0.943 | 0.937 | 0.961 | 0.972 | 0.991 | 0.961 | 0.924 | 6.0 | 12 | 2 |
| Jiangsu | 0.940 | 0.954 | 0.872 | 0.894 | 0.957 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 4.6 | 11 | 1 |
| Zhejiang | 0.870 | 0.770 | 0.785 | 0.805 | 0.864 | 0.870 | 0.902 | 0.966 | 0.954 | 0.965 | 0.997 | 12.6 | 26 | 2 |
| Fujian | 0.884 | 0.808 | 0.906 | 0.919 | 0.939 | 0.908 | 0.871 | 0.906 | 0.925 | 0.902 | 0.929 | 11.6 | 19 | 8 |
| Shandong | 0.759 | 0.827 | 0.845 | 0.823 | 0.854 | 0.881 | 0.883 | 0.876 | 0.823 | 0.803 | 0.883 | 18.5 | 24 | 12 |
| Guangdong | 0.935 | 0.859 | 0.902 | 0.929 | 0.941 | 0.935 | 0.916 | 0.945 | 0.982 | 0.914 | 0.883 | 9.2 | 17 | 3 |
| Hainan | 0.670 | 0.639 | 0.741 | 0.724 | 0.801 | 0.866 | 0.794 | 0.858 | 0.892 | 0.854 | 0.958 | 21.4 | 30 | 6 |
| InnerMongolia | 0.819 | 0.880 | 0.850 | 0.789 | 0.786 | 0.780 | 0.776 | 0.750 | 0.720 | 0.763 | 0.807 | 23.7 | 28 | 13 |
| Guangxi | 0.964 | 0.755 | 0.816 | 0.878 | 0.797 | 0.852 | 0.866 | 0.927 | 0.876 | 0.836 | 0.887 | 16.5 | 25 | 4 |
| Chongqing | 0.806 | 0.87 | 0.857 | 0.770 | 0.819 | 0.804 | 0.810 | 0.854 | 0.818 | 0.810 | 0.809 | 21.5 | 26 | 15 |
| Sichuan | 0.872 | 0.875 | 0.904 | 0.870 | 0.855 | 0.825 | 0.875 | 0.944 | 0.974 | 0.885 | 0.982 | 11.9 | 22 | 3 |
| Guizhou | 0.870 | 0.922 | 0.880 | 0.877 | 0.951 | 0.944 | 0.968 | 0.862 | 0.824 | 0.899 | 0.874 | 12.5 | 21 | 3 |
| Yunnan | 0.861 | 0.998 | 0.910 | 0.845 | 0.857 | 0.899 | 0.870 | 0.923 | 0.936 | 0.903 | 0.976 | 10.7 | 17 | 1 |
| Shaanxi | 0.806 | 0.899 | 0.840 | 0.838 | 0.792 | 0.768 | 0.747 | 0.805 | 0.904 | 0.883 | 0.888 | 19.5 | 27 | 12 |
| Gansu | 0.859 | 0.952 | 0.987 | 0.987 | 0.999 | 0.971 | 0.890 | 0.903 | 0.863 | 0.806 | 0.817 | 11.3 | 24 | 2 |
| Qinghai | 0.787 | 0.763 | 0.906 | 1.000 | 0.990 | 0.990 | 0.968 | 0.983 | 0.966 | 0.983 | 0.972 | 7.5 | 23 | 1 |
| Ningxia | 0.999 | 0.996 | 0.979 | 1.000 | 0.998 | 0.986 | 0.905 | 0.844 | 0.919 | 0.921 | 0.950 | 6.2 | 21 | 1 |
| Xinjiang | 0.722 | 0.766 | 0.829 | 0.824 | 0.847 | 0.868 | 0.822 | 0.825 | 0.819 | 0.785 | 0.813 | 21.9 | 26 | 17 |
| Shanxi | 0.944 | 0.931 | 0.935 | 0.940 | 0.950 | 0.919 | 0.894 | 0.896 | 0.851 | 0.875 | 0.871 | 11.3 | 21 | 5 |
| Anhui | 0.896 | 0.982 | 0.884 | 0.853 | 0.827 | 0.835 | 0.911 | 0.930 | 0.975 | 0.918 | 0.935 | 10.7 | 21 | 4 |
| Jiangxi | 0.710 | 0.713 | 0.754 | 0.818 | 0.738 | 0.759 | 0.707 | 0.743 | 0.817 | 0.818 | 0.871 | 25.5 | 29 | 19 |
| Henan | 0.791 | 0.762 | 0.798 | 0.789 | 0.801 | 0.819 | 0.826 | 0.813 | 0.852 | 0.809 | 0.875 | 21.8 | 24 | 18 |
| Hubei | 0.856 | 0.934 | 0.996 | 0.983 | 0.961 | 0.994 | 0.991 | 0.985 | 0.955 | 0.917 | 0.936 | 5.9 | 16 | 2 |
| Hunan | 0.727 | 0.802 | 0.868 | 0.818 | 0.792 | 0.765 | 0.781 | 0.804 | 0.800 | 0.760 | 0.839 | 23.8 | 27 | 16 |
| Liaoning | 0.829 | 0.845 | 0.867 | 0.888 | 0.877 | 0.918 | 0.840 | 0.763 | 0.743 | 0.729 | 0.767 | 19.5 | 28 | 11 |
| Jilin | 0.624 | 0.693 | 0.728 | 0.711 | 0.732 | 0.726 | 0.656 | 0.659 | 0.612 | 0.580 | 0.647 | 29.8 | 30 | 29 |
| Heilongjiang | 0.673 | 0.719 | 0.793 | 0.759 | 0.754 | 0.757 | 0.655 | 0.681 | 0.702 | 0.622 | 0.718 | 28.3 | 30 | 25 |

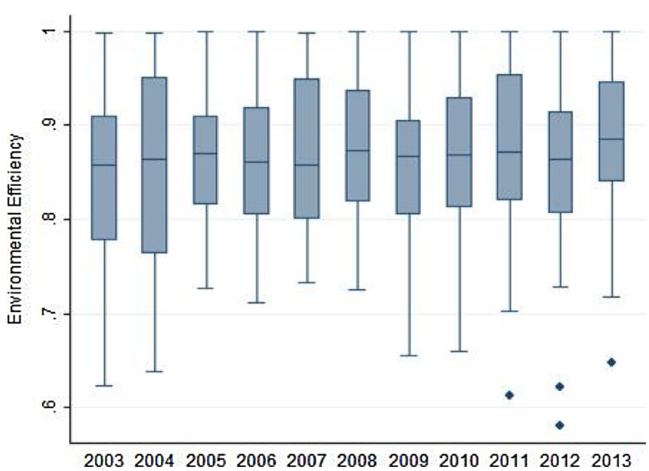


**Fig. 1.** The statistic properties of environmental efficiency in China's provincial generation sector during 2003–2013.
Note: The box-chart give the median, first quartile (x0.25) and third quartile (x0.75) of the data by using the lines in a box in Fig. 1. The interquartile rage (IQR) is calculated by subtracting the first quartile from the third quartile (x0.75 – x0.25). The smallest, largest and the average values line inside the figure with symbols.

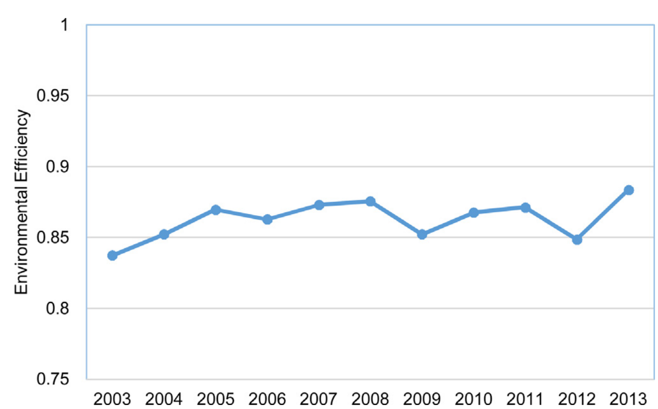


**Fig. 2.** The average environmental efficiency of China's generation sector during 2003–2013.

that this method performs well in discriminating the DMUs and can sort the results in a specific order. Meanwhile, Fig. 1 displays the statistical properties of the environmental efficiency. As can be seen, the range of efficiency narrows at first, next enlarges, and then narrows again at last. Because the ceiling of the environmental efficiency calculated by game cross-efficiency is unity; the variation range is determined by the floor. Combining the efficiency with the electricity supply and demand situation, it can be concluded that the efficiency is relatively high during the periods of power shortage and vice versa. Take 2008 as an example. Due to global economic crisis, China's entire economy has been under the big negative impact, the tight in power supply and demand situation become loose at the end of that year, which continued to 2009 and there is a significant decline in the efficiency from 2008 to 2009. Similarly, the situation of power supply and demand was relaxed from 2011 to 2012, and the environmental efficiency declined as well. Despite of technology and management differences, all the provinces must be fully productive when power supply is insufficient, which enlarges the efficiency gap among provinces. In brief, the game cross-efficiency may exactly capture the influence of the external situation and reflect the production efficiency of the power system. It has proved to be extremely effective in analyzing the efficiency of the power system in a competitive market.

Of all the 330 samples, 37.2% of them stay at over 0.900 in terms of environmental efficiency, and the proportion of provinces that are more than 0.750 reaches 89.7%, indicating that the efficiencies differ slightly in most provinces. Fig. 2 shows that the average environmental efficiency, which can be got by summing the efficiencies

of all provinces in each year dividing by the number of provinces. It represents the environmental efficiency of China's generation sector during the study period. As can be seen from Fig. 2, this average environmental efficiency shows a rising trend. It increases from the lowest point of 0.838 in 2003 to the second highest efficiency of 0.875 in 2008 before slipping to 0.852 in 2009. Another trough appears in 2012, and then it rises to the peak of 0.883 over the study period in 2013. After the release of unbundling reform of 2002, the generation enterprises faced fierce competition, which incentivized them to enhance technology and management. In addition, the fast development of economy with GDP growth of over 10% results in a continuously increasing electricity demand, and its growth rate exceeds the growth rate of installed capacity, which facilitated the improvement of capacity utilization in the power industry and further promoted their efficiency. However, the outbreak of the U.S. subprime mortgage crisis seriously affected the global economy with China included. At the end of 2008, the economic growth decreased, and the electricity consumption growth rate also dropped from 14.4% to 5.6%.[11] Despite the introduction of the country's four trillion yuan economic stimulus plan, China's growth rate of power consumption declined due to the slowdown of GDP growth, and the average environmental efficiency of the power industry fell to its second lowest point. With economic growth back on track, the average efficiency has gradually picked up. However, the average efficiency in 2012 reduces to another low point when China's GDP growth rate hits its lowest point. Based on the aforementioned analysis, it can be found that the efficiency values have the same trend as the economic growth rate with a certain lag.

It is noteworthy that there are outliers below normal during 2011–2013 when the electricity was oversupplied. Jilin appeared to be abnormal in these three years, and Heilongjiang happened once in 2012. It should be noted that Jilin was the province with the most severe wind power curtailment in these three years (specific analysis is given in Section 5.1). This suggests that an unreasonable allocation of capacity not only failed to improve its efficiency but widened the gap with other provinces. In addition, technological progress leads to the improvement of the overall efficiency, and this also widens the gap between the backward provinces and the frontier. From 2005 to 2008, the distribution of efficiency narrowed and the lowest value exceeds 0.700 when serious power shortage happened. The first quartiles show an overall increasing trend, and they are over 0.800 in the study period except for the first two years; the third quartiles remain basically stable and have been fluctuating around 0.920; the medians change very slightly, ranging from 0.858 to 0.874. All of these three indicators are increasing during 2009–2013 except for 2012. Furthermore, the gap between the first and third quartiles narrows, which indicates that the efficiencies of the provinces are in a convergence trend. This implies that the corresponding measures, such as eliminating outdated power generation equipments and stricter environmental protective policies, have achieved their initial goals.

## 5. Discussions

### 5.1. Environmental efficiency gaps

Referring to climatic condition, geographical location and socioeconomic situation, the provinces are classified into different regions for comparative studies in order to better regional development policies. According to the regional definitions of the government's "11th Five-Year Plan" and a number of policy documents,[12] as well as the researches of Zhou et al. (2013) and Bi et al. (2014), the provinces studied are divided into four regions: the eastern, central, western, and northeastern regions.[13] In accordance with the regional division, this study calculates the average environmental efficiency and ranking of each region in order to explore their differences, as shown in Table 3 and Fig. 3.[14] Overall, the eastern region performs best in all the statistics, including the minimum, average, and quartile of efficiency. It has the best environmental performance with an average efficiency of 0.892 and the maximum efficiency of 0.928. Slightly unexpected, the performance of the generation sector in the western region perform better than that of the central region, and the worst performance appears in the northeastern region. Even the minimum average efficiency of the eastern region is higher than the maximum one of the northeastern region.

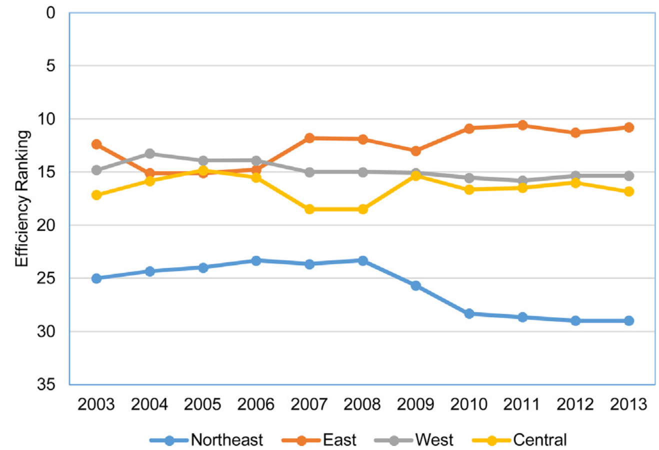


**Fig. 3.** The average environmental efficiency ranking of four regions during 2003–2013.

The differences in the environmental performance of the generation sectors across regions are closely related to the economic development. The eastern region was the first to carry out the reform and opening up policy and now is the most developed area in China. The economies of the central and western regions are relatively backward, but the implementation of the "Rising of Central China" and "Great Western development" strategies have promoted their economic development and narrowed the gap between them and the east region. The northeastern region, the old industrial base of China, relies heavily on the development of heavy industries such as the petroleum and coal industries. In recent years, there is an obvious economic downtrend in the northeastern region, partly because the traditional heavy industries have suffered from serious overcapacities. As these industries are the main power consumers, the economic situation leads to bigger gap between power supply and demand. Moreover, there is lack of strong environmental awareness and relevant measures for reducing emissions in that region, which all contribute to the low efficiency of the generation sector. The developed regions are in the better position to retrofit outdated capacity and to innovate and install advanced $CO_2$ emissions abatement technologies (Bian et al.,

[11] Source: National Bureau of Statistics (NBS) of China.

[12] The policy documents here refer to a series of strategic plans about "Rising of Central China", "Great Western development" and "Rejuvenating Northeast Old Industrial Base".

[13] The eastern region includes: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; Central: Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; Western: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang; Northeast: Liaoning, Jilin and Heilongjiang.

[14] The computing method for the average ranking of each region is similar to that for the national average environmental efficiency.

**Table 3**
Average environmental efficiencies and rankings for four regions during 2003–2013.

| Region | Min | | 1st Qu. | | Middle | | Mean | | 3rd Qu. | | Max | | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | E | R | E | R | E | R | E | R | E | R | E | R | |
| East | 0.852 | 10.6 | 0.871 | 11.1 | 0.896 | 11.9 | 0.892 | 12.5 | 0.911 | 13.9 | 0.928 | 15.1 | 11 |
| West | 0.851 | 13.3 | 0.869 | 14.4 | 0.879 | 15.0 | 0.875 | 14.8 | 0.881 | 15.4 | 0.889 | 15.8 | 11 |
| Middle | 0.821 | 14.8 | 0.849 | 15.7 | 0.854 | 16.5 | 0.857 | 16.5 | 0.870 | 17.0 | 0.888 | 18.5 | 11 |
| Northeast | 0.644 | 23.3 | 0.705 | 23.8 | 0.717 | 25.0 | 0.735 | 25.8 | 0.787 | 28.5 | 0.800 | 29.0 | 11 |

Note: E denotes environmental efficiency and R denotes ranking.

2013). With the increasing attention to the emission reductions, these areas are more likely to improve their technologies by active investment. For example, there are 139 thermal power units with an installed capacity of more than 600 MW in the eastern region, 49 in the western region, 42 in the central region, and only 14 in the northeastern region.[15] This is why the environmental efficiencies of the eastern provinces, such as Zhejiang and Jiangsu, have improved in recent years. In addition, the proportion of tertiary industries tends to be relatively large in the developed areas. Since the electricity consumption of tertiary industries is much less than that of secondary industries, it is easier for the generation sector of developed areas to get higher efficiency.

Moreover, the power mix has heavily affected the environmental efficiency. Hydropower, wind power, and other clean energy does not produce carbon emissions, so the areas where clean energy accounts for a large proportion usually have a higher environmental efficiency (Bi et al., 2014; Xie et al., 2012). The economy of the western region is close to or even less developed than that of the central region, but its overall efficiency is slightly higher due to the more optimized power mix. Because of its special geographic and climatic conditions, the western region is abundant in water and wind resources, whose proportion of thermal power is relatively low. Taking Qinghai as an example, over 70% of its power generation comes from hydropower, which is very special in China where the power mix is dominated by thermal power.[16] The cleanest power mix leads to the best environmental performance across the country on several occasions. There are 31 hydropower plants with an installed capacity of more than 1000 MW in the western region, while 9 and 10 in eastern and central regions, respectively, and only two in the northeast in 2013.[17] As a result, the western region performs better than the central and northeastern regions in environmental performance. A similar situation has occurred among the eastern region; the proportion of thermal power in Jiangsu has declined due to the promotion of renewable energy and “green power” since the 11th Five-Year Plan period, which has led to a sharp increase in environmental efficiency after 2008.

Furthermore, the power supply and demand situation is another crucial factor affecting the environmental efficiency. In the provinces with excess power generation, especially in the years with more frequent instances of wind power curtailment, the efficiency is generally low (Xie et al., 2012). For the rankings of provinces with large scale of wind power curtailment in recent years (Fig. 4), almost all of them experience a declining trend. Take the northeastern region as an example. Due to the unbalanced supply and demand situation and grid availability, the rate of wind curtailment in all three provinces has exceeded 10%, of which that in Jilin has reached 30%.[18] This grid absorption difficulty has resulted in a large amount of waste in clean energy investment and a decline in the profitability of power enterprises, which in turn greatly influenced the market competitiveness and production efficiency of the power generation sector. The environmental efficiencies of the aforementioned provinces were lower than the national average during the corresponding periods except for only a few provinces in the earlier years. China has implemented an investment plan of four trillion yuan in 2008, which has stimulated power investment in most of the provinces, especially the ones abundant in wind resources. As it is hard for wind power to work as peak loads, the curtailment is unavoidable. Simultaneously, the power consumption was not as high as expected due to the slowdown of economic growth after that. With the increase in supply and decrease in demand growth, it is difficult to absorb all the power generated, which results in a decline in efficiency in 2009 for most of the provinces mentioned previously. A province with surplus power can only sell its electricity to large enterprises at a very low price or transfer it to other provinces; as a result, the power generation sectors of these provinces are at a disadvantage in the competitive market and their efficiencies and rankings are lower than others. The environmental efficiency changes resulting from the power supply-demand situation are not only reflected at the provincial level but also at the national level, which has already been discussed also in Section 4.2.

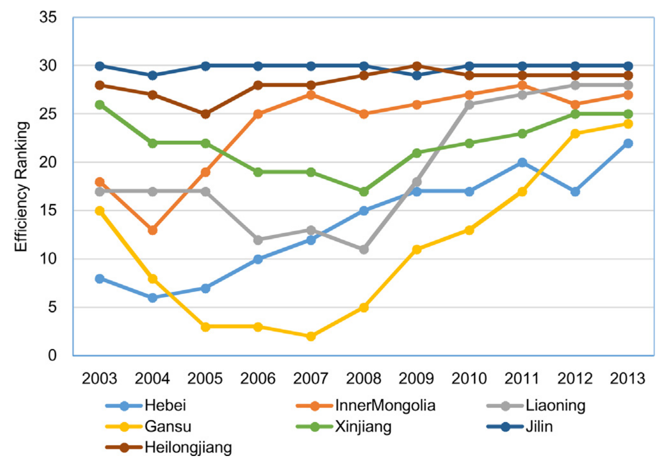


**Fig. 4.** The environmental efficiency ranking of the provinces with high wind power curtailment rates.

### 5.2. Determinants of environmental efficiency

In Section 5.1, this paper briefly analyzes the reasons for the environmental efficiency changes of the generation sector. Further research on related factors may help to identify the determinants of environmental performance, thereby enabling us to put forward some targeted policy implications. From the aforementioned analysis it can be concluded that the economic development, the power mix, and the supply–demand situation may affect the overall performance of generation sector. Meanwhile, this paper also refers to previous literature in choosing the potential influencing factors.

[15] Source: China Electric Power Yearbook 2014.
[16] Source: China Electric Power Yearbook 2004-2014.
[17] Source: China's Electric Power Industry Statistics Compiled 2014.
[18] Source: National Energy Administration at http://www.nea.gov.cn/.

**Table 4**
Definition of regression variables.

| Variables | Symbols | Unit | Definition |
|---|---|---|---|
| Environmental efficiency | E | | gained from game cross-efficiency model |
| Power mix | PM | % | thermal power generation/total power generation |
| Per capita region gross domestic product | PCRGDP | Yuan | per capita gross domestic product of each province |
| Average firm size | AFS | Yuan | total fixed-asset investment/number of enterprises |
| Capacity utilization rate | CUR | % | yearly utilization hours of installed capacity/total hours of the year |
| Industry structure | IS | % | the value-added of the second industry/total value-added of industry |

Accordingly, some relevant variables are stated in this section and the detailed explanations are as follows.

### 5.2.1. *Power mix* (PM)

Different generation forms differ greatly in technical efficiency and emission performance. China has a coal-dominant energy mix on the whole, but not all the provinces share the same power mix, and the thermal power ratio varies from less than 30% to 100% across provinces. This is a major concern in the studies regarding environmental efficiency (Xie et al., 2012; Zhou et al., 2013).

### 5.2.2. *Per capita regional gross domestic product* (PCRGDP)

Based on the analysis in Section 5.1 and other research results (Bi et al., 2014; Zhou et al., 2013), the regional economic development can affect the environmental efficiency of the power industry. In general, the regions with high *PCRGDP* have more advantages in research & development and equipment renewal than those with low *PCRGDP*.

### 5.2.3. *Average firm size* (AFS)

Many studies have advocated the unit scale as an indicator of the plant level (Du and Mao, 2015; Yang and Pollitt, 2009). In terms of the provincial level, Lin and Yang (2014) proposed to substitute it with the industry concentration in the power industry, and stated that the higher the industry concentration was, the larger the average scale of single enterprise was. This study adopts a similar concept and names it the average firm size.

### 5.2.4. *Capacity utilization rate* (CUR)

Considering the oversupply of electricity and the increasing generation capacity in recent years, it is essential to explore the impact of capacity utilization on the production of the generation sector. This study renders the *CUR* to indicate whether the generation capacity is fully utilized, and the higher it is, the less waste there is in the installed capacity.

### 5.2.5. *Industry structure* (IS)

The power consumption of the primary, secondary, and tertiary industries are quite different among provinces, especially in the secondary industry that includes a lot of enterprises with intensified energy consumption. The industry structure will affect the power absorption at the provincial level, which is expected to influence the environmental efficiency of the generation sector.

The detailed definitions of the regression variables are shown in Table 4. The data are collected from China's Electric Power Industry Statistics Compiled 2004–2014, National Bureau of Statistics, and Macro China Industry Database.

In order to unify the dimension, the aforementioned variables are normalized, and the formula (9) is executed to estimate the determinants of China's power industry environmental efficiency in 30 provinces from 2003 to 2013. And the results can be seen in Table 5.[19]

[19] See appendix A for the correlation coefficient matrix.

**Table 5**
Dynamic panel-data estimation for two-step system GMM.

| Number of instruments = 9<br>Dependent variables | E | |
|---|---|---|
| | Coef. | Std. Err. |
| E_lag1 | 0.546*** | 0.133 |
| PM | −0.307*** | 0.113 |
| PCRGDP | 0.161*** | 0.059 |
| AFS | −0.012 | 0.043 |
| CUR | 0.306*** | 0.092 |
| IS | 0.003 | 0.111 |
| Constant | 0.474*** | 0.127 |
| Diagnostic tests | Statistic | p value |
| AR(1) test | −3.33 | 0.001 |
| AR(2) test | −2.21 | 0.027 |
| AR(3) test | 1.63 | 0.103 |
| Wald test | 306.21 | 0.000 |
| Hansen test | 4.51 | 0.105 |
| Number of observations | 330 | |

Note.
*** Denotes statistical significance at the 1% level.

$$E_{i,t} = \alpha + \beta_0 E_{i,t-1} + \beta_1 PM_{i,t} + \beta_2 PCRGDP_{i,t} + \beta_3 AFS_{i,t} + \beta_4 CUR_{i,t} + \beta_5 IS_{i,t} + \nu_i + \varepsilon_{i,t} \tag{9}$$

The results of the Arellano–Bond test indicate that the error terms are not third-order serial correlated, which satisfies the hypothesis of SGMM; Hansen tests accept the null hypothesis due to the insignificant P-values at the 10% level, and the result of Hansen test is robust, demonstrating that the instrumental variables are valid; the Wald chi-square test confirms the overall significance of the regression specification, and the number of instruments has also been effectively controlled.

The external factors vary among regions, and they do affect the environmental efficiency of the generation sector. The coefficient of *PM* is negative at the 1% level significantly, implying a negative correlation between *E* and *PM*. Obviously, the environmental efficiency is strongly influenced by its power mix. As thermal power dominants the $CO_2$ emissions of the power industry, which results in the decline of environmental efficiency along with the increase of thermal power ratio.

*PCRGDP* and *CUR* have positive impacts on *E*. The *E* will increase by 0.161% when *PCRGDP* gets a growth of 1%. The trend of the energy demand, especially the power demand, is often consistent with the change in per capita GDP. The developed provinces usually have a greater energy demand, so it is more necessary to improve their electricity efficiency to meet the increased demand (Xie et al., 2012). Meanwhile, the appeal for environmental quality is relatively strong in the developed provinces, and they have both driving force and abilities to introduce or develop advanced technologies. As for *CUR*, *E* grows higher if the generation capacity is less idled while too much capacity may lead to low utilization rates and over competitiveness in the generation sector. As can be seen from Table 5,*E* increases by approximately 0.306% as *CUR* grows by 1%.

*PM*, *PCRGDP*, and *CUR* are all of statistically significant at the 1% level, and the coefficients have slight differences. The *E* rises by approximately 0.307%, 0.161% and 0.306%, respectively, as *PM*, *PCRGDP* and *CUR* increase by 1%. Comparatively, *PM* and *CUR* have greater impacts on *E*, implying that the efficiency revealed by the game cross-efficiency model is more affected by the power mix and power supply situation than other factors, and a power surplus always detracts from the operations of low-efficiency provinces. There is no doubt that an appropriate increase in the proportion of clean energy generation will improve environmental efficiency, but an overreliance on clean power may damage the stability of the grids and do harm to the development of the economy.

## 6. Conclusions and policy suggestions

### 6.1. Conclusions

This study employs a game cross-efficiency model to measure the environmental efficiency of China's generation sector from 2003 to 2013. Furthermore, it has adopted the SGMM method to eliminate the endogenous issues among the provinces and to analyze the determinants of environmental efficiency. This study reaches several conclusions as follows:

Incorporating game cross-efficiency with SGMM is an effective approach to measure the environmental efficiency of the generation sector. The game cross-efficiency results combining self-evaluation with peer-evaluation performed well in terms of discrimination and objectiveness. The number of efficient DMUs decreased significantly under the game cross-efficiency model. In contrast to other regression models, the SGMM may eliminate the influence of endogenous factors on efficiency. It is foreseeable to indicate that the competitiveness in the generation sector will be strengthened with the deepening of reforms, and this approach may gain popularity in not only the generation sector but also the transmission and distribution sectors.

Even though the efficiency gaps among regions decrease, it is hard to achieve simultaneous nationwide improvement in environmental efficiency. There exists a relatively large room to promote the efficiency of China's power industry. The average environmental efficiencies were less than 0.88 during 2003–2011; some efficiencies were even lower than 0.6, and there are outliers during 2011–2013 due to the power supply and demand situation changes. A power shortage always leads to a smaller gap, whereas a power surplus usually makes the operation of low efficiency provinces worse.

The *PCRGDP* and *CUR* are conducive to improving the environmental efficiency of the generation sector, whereas *PM* is negatively related to the efficiency. The power consumption is determined by *PCRGDP* to a great extent, which is the main driver beyond the power system control for efficiency improvement. The *CUR* reflects the utilization rate of equipment, which is also a driving force for the performance improvement that the industry may adopt measures to improve. Nevertheless, the development of clean energy may improve the environmental efficiency of the generation sector due to its contribution in reducing emissions.

### 6.2. Policy implications

Based on the aforementioned analysis, the following measures are proposed to improve the environmental efficiency of the generation sector.

First, it is urgent to adjust the efficiency evaluation mechanism to improve the environmental performance of the generation sector. Both power system development and energy-saving and emissions reduction are very important to China. A well-designed power management mechanism taking long-term and short-term factors as well as regional differences into consideration may help to achieve the sound development of the generation sector. Not only favorable policies for investment, as well as subsidies in central, western and northeastern regions with underdeveloped economies, but also the incentive policy for the eastern region to purchase green power generated by underdeveloped regions are effective measures to accelerate the national green electricity development, which in turn may narrow the differences among regions in environmental performance for the generation sectors.

Second, the power mix should be adjusted in step with the technology and local economic development. The improvement of the power mix cannot be simplified to monotonically decrease the thermal power ratio, – a balanced and coordinated power system with a variety of generation forms could not only fulfill the power demands but also achieve environmental efficiency improvement. There is no doubt that it is important to control the thermal power ratio within a reasonable range for newly installed capacity, but it does not mean that the green power ratio should be randomly improved. Compared to improving the clean power generation, it is very essential to encourage innovation, especially in the aspect of energy saving and emissions reduction.

Finally, it is important to make full use of the installed capacity, instead of installing new generator unit blindly due to the preferential subsidy policies. The development of electricity needs to match the local economic development, and it is not a good idea to exceed the demand for electricity too much. In this regard, incentive policies for research & development may perform better than subsidies from a long-term perspective.

However, there are also several aspects needing to be improved. For example, this study has not included other pollutants, such as $SO_2$ and $NO_x$, in examining the environmental efficiency of the power industry. In addition, it conducts the analysis with the provincial data rather than the plant level data, which is the actual operator of the generation sectors. Furthermore, the study has not examined the dynamic efficiency of the power industry. These issues will be studied in future research.

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## Appendix A

See Table A1.

**Table A1**
Correlation coefficients among independent variables in formula (9).

| Variable | PM | PCRGDP | AFS | CUR | IS |
|---|---|---|---|---|---|
| PM | 1.0000 | | | | |
| PCRGDP | 0.3119 | 1.0000 | | | |
| AFS | 0.1206 | 0.6056 | 1.0000 | | |
| CUR | 0.4449 | −0.1062 | −0.0241 | 1.0000 | |
| IS | 0.1221 | 0.0183 | 0.0144 | 0.2603 | 1.0000 |

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